A Cellular Automata Markov (CAM) model for land use change prediction using GIS and Python

by

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ABSTRACT

Knowledge of future land use changes is crucial, as they are interlinked to various factors of human-environmental systems. Spatial data can often be computationally heavy, so the provision of accessible and ready-to-use tools is crucial for the analysis of land use changes in any case study. In this work, a Cellular Automata Markov (CAM) model is presented and applied through a combination of Geographic Information Systems (GIS) and Python, to predict land changes and provide future land use maps. The inputs are historical land use maps at a five-year time-step from 2006 to 2021, and the outputs include future land use maps until 2051, again at a five-year time-step. Various validation techniques are explored for the predicted maps, based on the historical data, including Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the Kappa coefficient (κ), and Confusion Matrix statistics. A step-by-step GIS guide and the Python script are provided with screenshots and explanations, to contribute to the reproducibility and improvement of the presented model.

Keywords: Land uses; Cellular Automata Markov model; GIS; Python; Prediction; Validation.

INTRODUCTION

Studying the future changes of land uses in specific areas is indispensable due to their intricate connections with various aspects dynamically affecting human-environmental systems. Land use changes have a profound impact on urban planning, environmental sustainability, resource management, and overall quality of life (Liu et al., 2022; Hassan and Nazem, 2016). Understanding these changes is vital for making informed decisions that affect population growth, resource availability and use, infrastructure development, and natural capital and biodiversity conservation, among others (McDermott et al., 2022). Moreover, anticipating shifts in land use patterns enables policymakers to address challenges such as urban sprawl, deforestation, and habitat loss (Hassan and Nazem, 2016; McDermott et al., 2022). In an era marked by urbanization, climate change, and resource constraints, the ability to foresee and manage land use changes is a crucial asset for building resilient and sustainable communities while safeguarding our planet's ecosystems.

The most common technique to explore future land uses is the Cellular Automata (CA), based on Markov-chain modelling, called Cellular Automata Markov (CAM) models (Aburas et al., 2019). The logic of CA models is to simulate land use changes by considering the local interactions between cells (geographic units in spatial datasets). They are based on transition rules (e.g., changes over a period of time), and initial conditions (i.e., compared to an initial base-year). Markov chain models rely on the assumption that future land use depends on the current state (base year map) and is independent of past states. Thus,

CAM models use historical data, usually in the form of maps, to derive transition rules, namely transition probability matrices among the land use categories, and generate future maps by applying these matrices as rules, iteratively to the historic data (Corner et al., 2013). The field is fast developing, and more complex methodologies occur, such as combinations of CAM and Geographic Information Systems (GIS) with Remote Sensing observations (Islam and Ahmed, 2012), machine learning techniques (Xing et al., 2020; Zambrano-Asanza et al., 2023), and Multi-Criteria Analysis techniques (Addae and Dragićević, 2022), for improved prediction accuracies and/or the consideration of more factors in the analyses. The validation of the projections is performed statistically, comparing the historic data with the predicted ones, for the same year(s), and the most commonly used measure is the Kappa statistics, assessing the accuracy of the projections (Saputra and Lee, 2019; Liu et al., 2021).

There have been several CAM modelling applications, for urbanization projections (Ulloa-Espíndola and Martín-Fernández, 2021; Mansour et al., 2020), for the evaluation of different development scenarios (Han et al., 2015), agriculture and biodiversity management (Halmy et al., 2015), the impact of climatic parameters (Tariq and Shu, 2020; Al Kafy et al., 2021), etc. Moreover, future land uses can be necessary for a variety of other analyses, such as soil and hydrological assessments (Anard et al., 2018; Dai et al., 2023), wetland management (Ansari and Golabi, 2019; Alamanos and Papaioannou, 2020), urban and rural development (Agustina et al., 2022; Alamanos et al., 2022a; 2022b), flood risk assessments (Roy et al., 2020; Papaioannou et al., 2023), ecological assessments (Qin and Fu, 2019), optimal agricultural management (Garcia and Alamanos 2022; 2023), management of transboundary environmental and economic assets (Englezos et al., 2023; Mendoza-Poce et al., 2021), and many more. The importance of having reliable land use change models is widely recognized, and the provision of user-friendly tools is crucial. However, there are very few available free and publicly accessible tools for such processes, and this work aims to fill this gap: Facilitate the integration of land use changes in a variety of studies, and respond to the need for accessible tools and transparent methodologies to support informed decision-making in diverse environmental planning projects.

In this paper, a CAM model is presented, as a combination of processes in GIS environment and open-source coding, using Python. The tool uses the minimum number of inputs, namely historic land use maps, and generates future land use maps. The approach presented is publicly available (data, GIS guide with screenshots, and Python script), contributing to the provision of tools for land use prediction, and highlighting the significance of using such modeling techniques within the broader context of human-environmental systems management.

STUDY AREA

The Cedar Creek Watershed (CCW) in Indiana, US, is used as a case study to apply the modelling framework presented. Cedar Creek, is located in northeastern Indiana, and is an area of great natural beauty within the St. Joseph River watershed. It encompasses a diverse landscape of farms, urban areas with cities and settlements, and notable geological features (CCW Management Plan, 2005). Positioned just north of Fort Wayne, Indiana's second-largest city, Cedar Creek flows into the St. Joseph River, where Fort Wayne sources its drinking water downstream. CCW covers approximately 700 km², it has a gentle sloping topography and is primarily used for agriculture (mainly corn, soybeans, and other crops) (Pignotti et al., 2017). The region experiences an average temperature range of -1 to 28°C with an annual

precipitation of 940 mm (Wallace et al., 2018). The land uses have been traditionally agricultural, with a slight increase of urban areas, while forests and water bodies are also present (Figure 1).

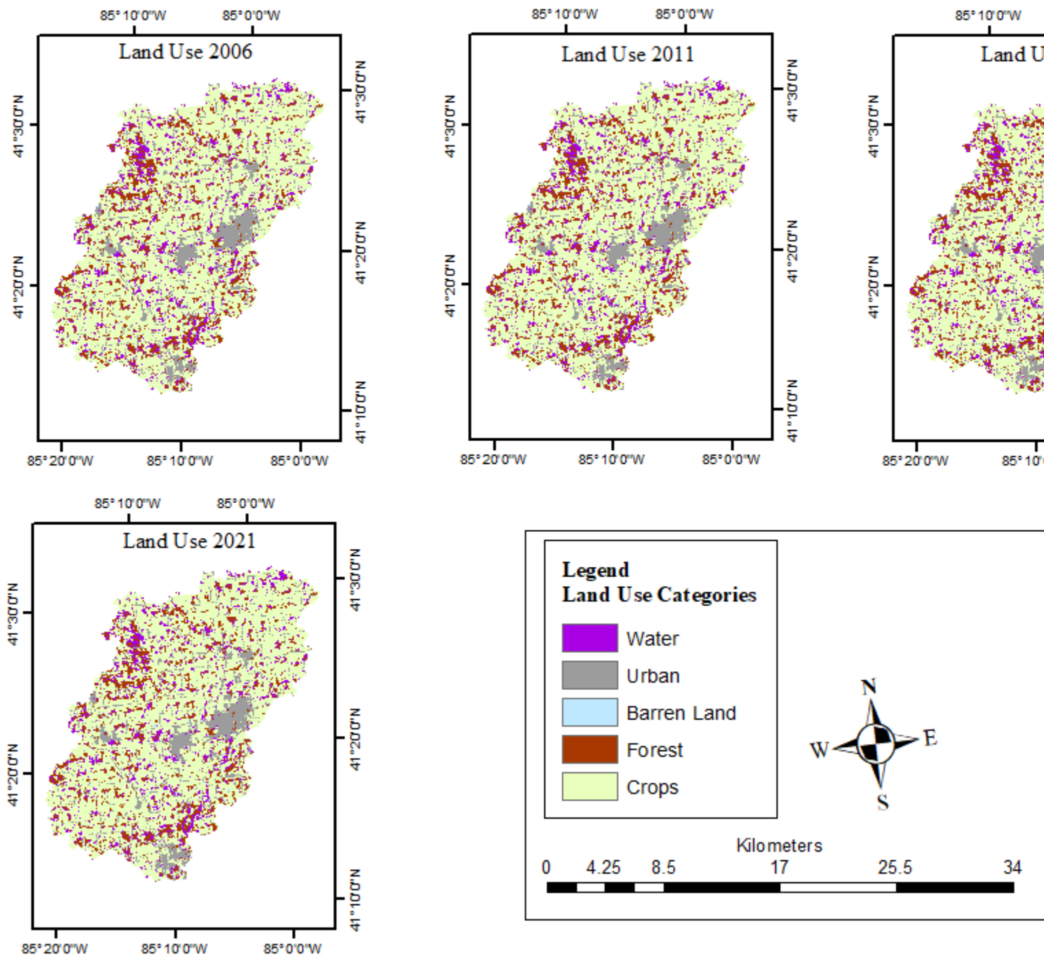

Figure 1. The land uses of CCW from 2006 to 2021.

METHODOLOGY

<u>Input Data and preprocessing</u>

The input data of land uses were obtained from the United States Geological Survey (USGS) website (USGS, 2021), as shape files for the years 2006, 2011, 2016 and 2021 for Cedar Creek (Indiana, USA). The data resolution (cell size (X,Y)) is 30x30, and come in a default coordinate projected system of GCS_WGS_1984. We used the Digital Elevation Model (DEM) of the watershed (CCW) as a 'mask' in GIS (ArcMap 10.7.1), to <u>*clip*</u> the full land use map into just the part referring to our watershed. So, we got the land uses for only the CCW area. For the purpose of this example, the data for the land uses and DEM are provided in the folder 'data'. The main land use categories that were analyzed in this example were: 'Water': 1, 'Urban': 2, 'Barren Land': 3, 'Forest': 4 and 'Crops': 5. Working with the main (e.g. 5) land use classes reduces the computational load and effort, and allows to handle easier the land use changes from year to year.

The Cellular Automata Markov (CAM) model

Creating a Cellular Automata Markov (CAM) model for land use change prediction involves the estimation of the transition probability matrix, and simulation of land use changes over time. The CAM model can be mathematically represented as follows:

$$L_{t+1} = P_{ij} \cdot L_t \text{ , for land use types i,j = 1,2,…,n} \tag{1}$$

Where L_t and L_{t+1} are the land use maps at the year t and t+1 respectively, and P_{ij} is the transition probability matrix expressing the probability of each cell (pixel) to change from the land use type i in the year t to the land use type j in year t+1. So, this matrix can be expressed as follows:

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & & & \cdots \\ P_{n1} & \cdots & \cdots & P_{nn} \end{bmatrix} \text{, with } 0 \leq P_{ij} \leq 1 \text{, and } \sum_{i,j=1}^{n} P_{ij} = 1 \tag{2}$$

Practically, the transition probability matrix is estimated by “cross-tabulation” of two maps from different years (t, t+1), and it determines the probability of a pixel in a land-use class i to change into another class j during that time. To estimate these probabilities, we need first to know the number of pixels that changed from each land use i to another type j, over time. Namely, this process returns each element of the change (transition change) matrix (not as probability though, i.e. not the P_{ij} matrix, just as cells changed). These changes were calculated within GIS with the “*Tabulate Area*” tool, based on the historic data (land use maps of 2006, 2011, 2016, 2021). These normalized Change Matrices consist the final Transition Probability Matrices (P_{ij}) for each pair of years studied.

Having the Transition Probability Matrices, the CAM model can be applied to predict future land uses, as described in Equation 1, using the results obtained for Equation 2 (P_{ij}). The L_t in Equation 1 is going to be the historic land use map. This process results in the final land use map of the desired year (L_{t+1}) with the defined land use categories.

Validation

Validating the predicted land use maps is an essential step to assess the accuracy of the model and make future predictions ‘safely’. There are many techniques that can be used, such as statistical tests based on:

- Percentage of Accurate Results (Overall Accuracy):

  Overall accuracy is a straightforward measure that calculates the percentage of correctly classified pixels compared to the total number of pixels. It provides a clear and easily interpretable metric of the model's accuracy (0 = bad, 1 = perfect). Practically, it is the percentage of correctly classified data points (pixels, in this case) compared to the total number of data points (Equation 3):

$$Accuracy = \frac{Number\ of\ Correctly\ Classified\ Data\ Points}{Total\ Number\ of\ Data\ Points} \times 100\% \tag{3}$$

- Mean Absolute Error (MAE):

It quantifies the magnitude of errors between predicted and actual land use values. Lower MAE values indicate better model performance (closer to 0 is perfect). It is expressed as the average absolute difference between the actual and the predicted values (Equation 4):

$$MAE = \frac{1}{Total\ Number\ of\ Data\ Points} \sum_{point\ 1}^{point\ N} |actual - predicted| \tag{4}$$

- Root Mean Square Error (RMSE):

It measures the square root of the average squared difference between predicted and observed values. It penalizes larger errors more heavily than smaller ones. Lower RMSE values indicate better model performance (closer to 0 is perfect). It is expressed as the average magnitude of errors or residuals between predicted values and observed values. In the context of land use classification, RMSE can be used to quantify how close the predicted land use categories are to the true land use categories on average (Equation 5):

$$RMSE = \sqrt{\frac{1}{Total\ Number\ of\ Data\ Points} \sum_{point\ 1}^{point\ N} (predicted - actual)^{2}} \tag{5}$$

- Kappa (κ):
  Cohen's Kappa measures the level of agreement between two raters or classifiers, often used in the context of classification tasks like land use mapping. It quantifies the agreement between the predicted and true labels while taking into account the possibility of agreement occurring by chance (Equation 6):

$$\kappa = \frac{Po - Pe}{1 - Pe} \tag{6}$$

Where:

- Po is the observed agreement between the predicted and true land use categories. It represents the proportion of instances where the predicted and true labels match.
- Pe is the expected agreement between the predicted and true land use categories, if their agreement were purely due to random chance. It is calculated as the product of the proportions of each label predicted and true, summed over all possible label pairs.

Kappa ranges from -1 to 1:

- A value of 1 indicates perfect agreement between the predicted and true labels.
- A value of 0 indicates agreement that is no better than chance.
- A negative value indicates agreement worse than chance.

- Confusion matrix:

This is a common tool used in classification problems to evaluate the performance of a classification model. It provides a tabular representation of the classification results, showing the number of:

- true positives (TP) which are the correctly predicted cells,
- true negative (TN) which are the correctly predicted cells that were correctly classified as a class other than the specific class,
- false positive (FP) which are the pixels that were incorrectly classified as a specific class,
- false negative (FN) incorrectly classified in other classes.

Based on these values we can estimate also the:

- Precision. This measures the accuracy of positive predictions. For each land use category, it's the ratio of correctly predicted samples of that category to all samples predicted as that category.
- Recall. This measures the ability of the classifier to correctly identify all relevant instances (true positives). For each land use category, it's the ratio of correctly predicted samples of that category to all actual samples of that category.
- F1-score. This is the harmonic mean of precision and recall. It provides a balance between precision and recall and is particularly useful when dealing with imbalanced datasets.

RESULTS AND DISCUSSION

A Python script (Spyder, Anaconda) was used to process the historic land use maps, estimate the transition probability matrix, and generate the predicted maps. The script uses the results of the GIS "*Tabulate Area*" tool, normalizes their values and returns the transition probability matrices for each year studied. Indicatively, the resulted transition probability matrices for each time-step of the historic years 2006-2021, are:

• transition_probability_matrix1 (2006 to 2011): [[0.9905 0.0007 0.0003 0.001 0.0076] [0. 1. 0. 0. 0.] [0.0217 0.0145 0.9614 0. 0.0024] [0.0015 0.0013 0. 0.9909 0.0063] [0.0009 0.0027 0. 0.0005 0.9959]]	• transition_probability_matrix2 (2011 to 2016): [[0.99 0.0005 0.0005 0.0015 0.0075] [0. 1. 0. 0. 0.] [0.0434 0.0137 0.9384 0.0046 0.] [0.0015 0.001 0. 0.9907 0.0069] [0.0008 0.0028 0. 0.0002 0.9962]]	• transition_probability_matrix2 (2016 to 2021): [[0.9984 0.0005 0.0006 0.0005 0.0001] [0. 0.9998 0. 0. 0.0002] [0.0089 0.0201 0.9284 0.0425 0.] [0.0004 0.0021 0. 0.9952 0.0023] [0.0004 0.0024 0.0015 0. 0.9956]]

The CAM model was applied in a 5-year time-step until 2051, according to Equation 1, for each time step (2011 to 2016, 2016 to 2021, 2021 to 2031, 2031 to 2036, 2036 to 2041, 2041 to 2046, 2046 to 2051), using the respective transition probability matrices. Thus, the results predicted are land use maps for 2026, 2031, 2036, 2041, 2046 and 2051 (Figure 2). The process continued iteratively for each time step until the desired year (2051), updating the transition probability matrices each time, based on changes observed in the validation process. Transition matrices can be adjusted to better reflect changes in land use dynamics.

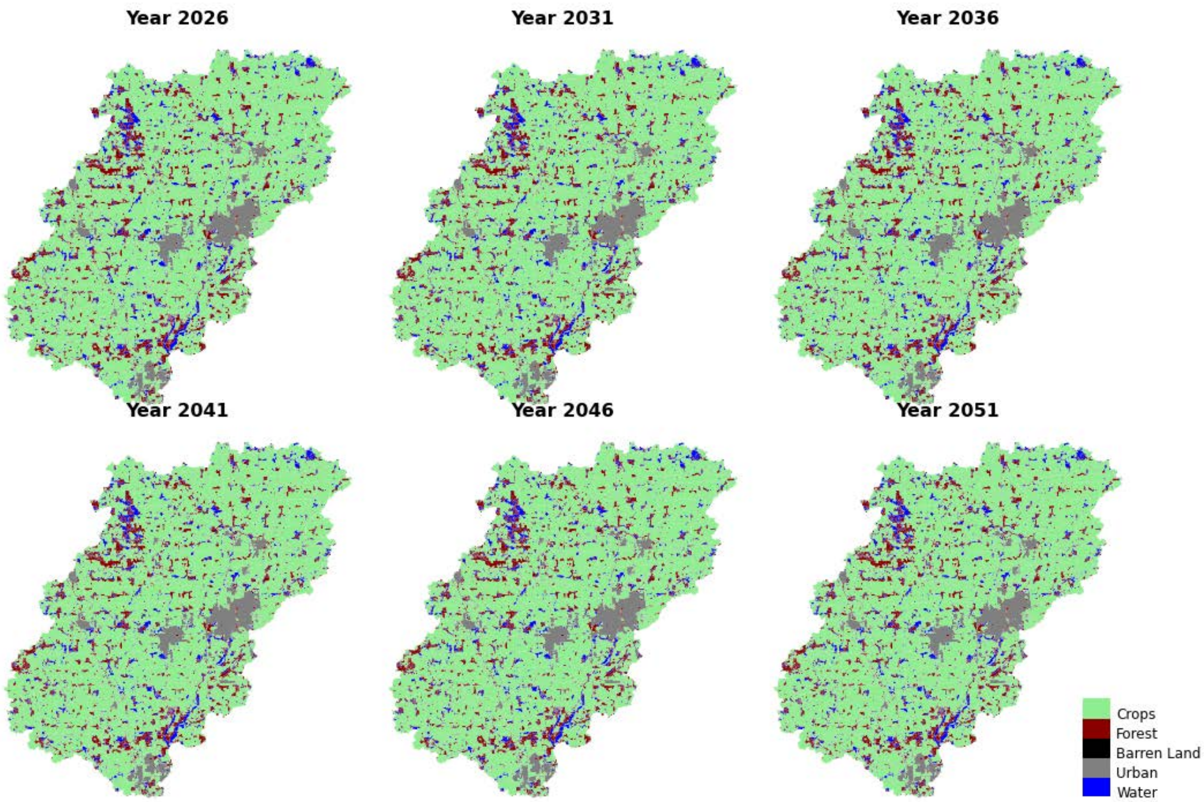

Figure 2. The predicted land use maps for CCW from 2026 to 2051.

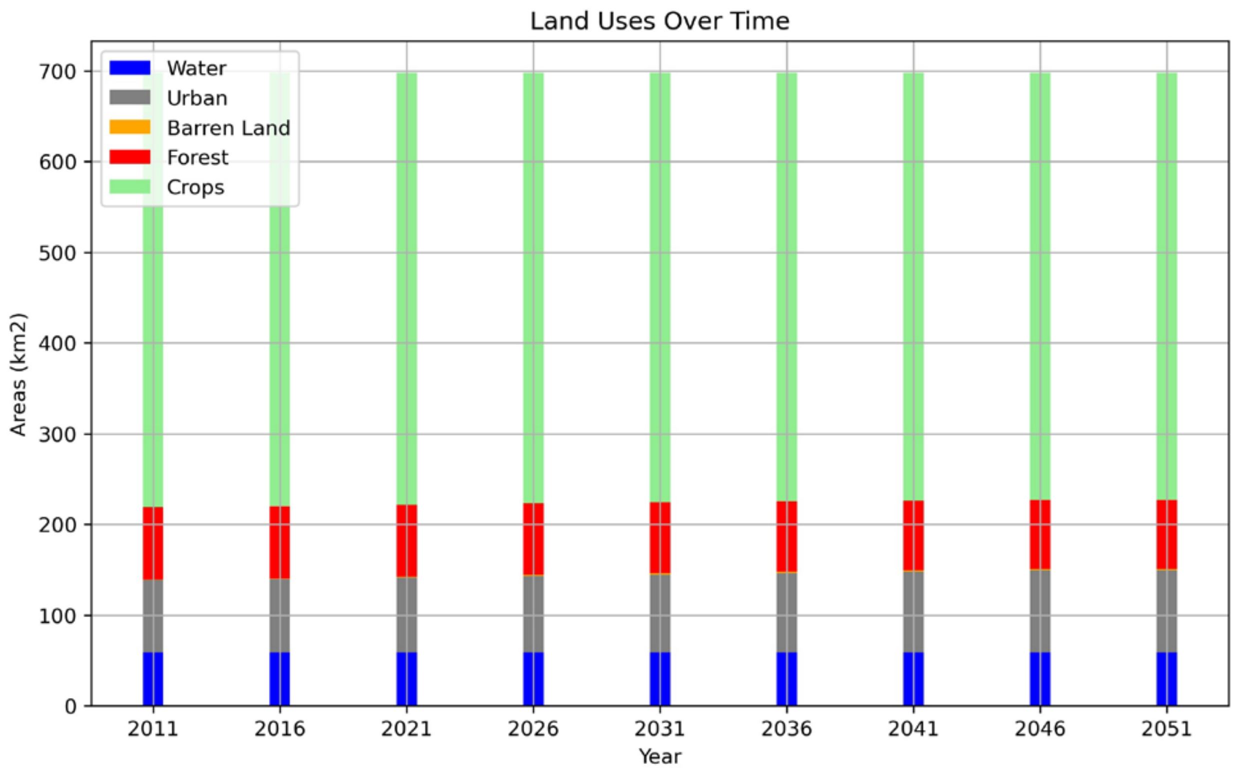

Figure 3. The historic and predicted land use maps for CCW from 2011 to 2051.

The validation of the predicted maps is show in the Table 1 below, summarizing all the statistic measures used.

Table 1. The Confusion Matrix, the Accuracy, the MAE, the RMSE, and the Kappa coefficient of the predicted results.

Confusion Matrix	**Water (1)**	**Urban (2)**	**Barren land (3)**	**Forest (4)**	**Crops (5)**
Water (1)	65004	30	41	32	4
Urban (2)	1	90347	0	1	18
Barren land (3)	4	9	415	19	0
Forest (4)	33	184	4	87936	199
Crops (5)	214	1274	816	15	528808
Accuracy:			0.9963		
MAE:			0.0094		
RMSE:			0.1613		
Kappa:			0.9925		

Table 1 shows that the Accuracy was very good, 99.63%, same for the Kappa coefficient. Also, the MAE and RMSE showed the good model performance, being close to zero values.

The confusion matrix can be interpretated as follows:

Water (1):

- True Positives (TP): 65,004 - These are water pixels that were correctly classified as water.
- False Negatives (FN): 30 + 41 + 32 + 4 = 107 water pixels that were incorrectly classified as something other than water.

Urban (2):

- True Positives (TP): 90,347 - These are urban pixels that were correctly classified as urban.
- False Negatives (FN): 1 + 0 + 1 + 18 = 20 urban pixels that were incorrectly classified as something other than urban.

Barren land (3):

- True Positives (TP): 415 - These are barren land pixels that were correctly classified as barren land.
- False Negatives (FN): 4 + 9 + 19 + 0 = 32 barren land pixels that were incorrectly classified as something other than barren land.

Forest (4):

- True Positives (TP): 87,936 - These are forest pixels that were correctly classified as forest.
- False Negatives (FN): 33 + 184 + 4 + 199 = 420 forest pixels that were incorrectly classified as something other than forest.

Crops (5):

- True Positives (TP): 528,808 - These are crop pixels that were correctly classified as crops.
- False Negatives (FN): 214 + 1274 + 816 + 15 = 2,319 crop pixels that were incorrectly classified as something other than crops.

The classification report from the confusion matrix is presented in Table 2.

Table 2. The Classification Report. For all categories the min= 0 (worst performance) and the max =1 (best performance). The 'Support' expresses the number of actual samples in each category.

Class	Precision	Recall	F1-score	Support
1 (Water)	1.00	1.00	1.00	65111
2 (Urban)	0.98	1.00	0.99	90367
3 (Barren Land)	0.33	0.93	0.48	447
4 (Forest)	1.00	1.00	1.00	88356
5 (Crops)	1.00	1.00	1.00	531127

CONCLUSIONS

This exercise showcased how a CAM model using GIS and Python can be applied to future land use predictions, as well as their validation. As explained in the introductory section, this analysis can find multiple applications in a variety of studies on human-environmental systems.

It is important to keep in mind that the behavior of a CAM model always depends on the specific rules and parameters set for the model. For example, one could expect a concentrated urbanization around the existing urban centers rather than a more scattered picture. The CAM model works on a pixel-by-pixel basis and does not inherently consider the spatial distribution of land use changes unless explicitly programmed to do so. It uses factors such as the current land use category of a pixel, its neighboring pixels and the transition probabilities (according to the estimated matrices). For more refined changes, factors like proximity to existing urban centers, can be included in the code. In this case, we kept the example simple, as proximity to existing urban centers would require additional data (e.g. shape files or point data of urban centers), and extra analysis (e.g. raster-distance tools, using the proximity as an additional layer, and incorporate it in the CAM). Moreover, the methodology used for conversion and transition may not accurately reflect the real-world land use dynamics, that are connected with other external factors (e.g. economics, behavioural drivers, etc.). In any case, the validation over historic land use observations helps to ensure a degree of accuracy of the model and make improvements by further adjusting it (mainly through the transition probability matrices). In this case, the validation showed a good performance of the model.

The data used in this example, the file with the basic steps/ processes executed in GIS and in the script with screenshots, and the codes used are also provided. Further research with more land use classes, improved adjustments of the transition probability matrices, or considering more factors like the role of the neighboring cells would be very useful to further improve the prediction of land use maps.

Data and Code Availability, including Supporting Information:

https://github.com/Alamanos11/Land_uses_prediction

REFERENCES

Aburas, M. M., Ahamad, M. S. S., & Omar, N. Q. (2019). Spatio-temporal simulation and prediction of land-use change using conventional and machine learning models: A review. *Environmental Monitoring and Assessment*, *191*(4), 205. https://doi.org/10.1007/s10661-019-7330-6

Addae, B., & Dragićević, S. (2022). Integrating multi-criteria analysis and spherical cellular automata approach for modelling global urban land-use change. *Geocarto International*, *0*(0), 2152498. https://doi.org/10.1080/10106049.2022.2152498

Agustina, I. H., Aji, R. R., Fardani, I., Rochman, G. P., Ekasari, A. M., & Mohmed, F. A. J. (2022). CELLULAR AUTOMATA FOR CIREBON CITY LAND COVER AND DEVELOPMENT PREDICTION. *PLANNING MALAYSIA*, *20*. https://doi.org/10.21837/pm.v20i20.1080

Alamanos, A., & Papaioannou, G. (2020). A GIS Multi-Criteria Analysis Tool for a Low-Cost, Preliminary Evaluation of Wetland Effectiveness for Nutrient Buffering at Watershed Scale: The Case Study of Grand River, Ontario, Canada. *Water*, *12*(11), Article 11. https://doi.org/10.3390/w12113134

Alamanos, A., Koundouri, P., Papadaki, L. & Pliakou, T. (2022a). Digital management of irrigation water and agriculture: Transparency and accountability towards resilience and sustainable development. IAHR Youth Water Congress - "Youth in the forefront: before and after World Water Forum, Emerging water challenges since COVID-19". 6-8 April, 2022.

Alamanos, A., Koundouri, P., Papadaki, L., Pliakou, T. & Toli, E. (2022b). Digital agricultural management tools for efficient and integrated policy-making. 1st International Electronic Conference on Land (IECL2022). Online, 17–19 May 2022.

Anand, J., Gosain, A. K., & Khosa, R. (2018). Prediction of land use changes based on Land Change Modeler and attribution of changes in the water balance of Ganga basin to land use change using the SWAT model. *Science of The Total Environment*, *644*, 503–519. https://doi.org/10.1016/j.scitotenv.2018.07.017

Ansari, A., & Golabi, M. H. (2019). Prediction of spatial land use changes based on LCM in a GIS environment for Desert Wetlands – A case study: Meighan Wetland, Iran. *International Soil and Water Conservation Research*, *7*(1), 64–70. https://doi.org/10.1016/j.iswcr.2018.10.001

Corner, R. J., Dewan, A. M., & Chakma, S. (2014). Monitoring and Prediction of Land-Use and Land-Cover (LULC) Change. In A. Dewan & R. Corner (Eds.), *Dhaka Megacity: Geospatial Perspectives on Urbanisation, Environment and Health* (pp. 75–97). Springer Netherlands. https://doi.org/10.1007/978-94-007-6735-5_5

Dai, D., Alamanos, A., Cai, W., Sun, Q., & Ren, L. (2023). Assessing Water Sustainability in Northwest China: Analysis of Water Quantity, Water Quality, Socio-Economic Development and Policy Impacts. *Sustainability*, *15*(14), Article 14. https://doi.org/10.3390/su151411017

Englezos, N., Kartala, X., Koundouri, P., Tsionas, M., & Alamanos, A. (2023). A Novel HydroEconomic—Econometric Approach for Integrated Transboundary Water Management Under Uncertainty. *Environmental and Resource Economics*, *84*(4), 975–1030. https://doi.org/10.1007/s10640-022-00744-4

Garcia, J. A., & Alamanos, A. (2022). Integrated Modelling Approaches for Sustainable Agri-Economic Growth and Environmental Improvement: Examples from Greece, Canada and Ireland. *Land*, *11*(9), Article 9. https://doi.org/10.3390/land11091548

Garcia, J. A., & Alamanos, A. (2023). A Multi-Objective Optimization Framework for Water Resources Allocation Considering Stakeholder Input. *Environmental Sciences Proceedings*, *25*(1), Article 1. https://doi.org/10.3390/ECWS-7-14227

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, *63*, 101–112. https://doi.org/10.1016/j.apgeog.2015.06.015

Han, H., Yang, C., & Song, J. (2015). Scenario Simulation and the Prediction of Land Use and Land Cover Change in Beijing, China. *Sustainability*, *7*(4), Article 4. https://doi.org/10.3390/su7044260

Hassan, M. M., & Nazem, M. N. I. (2016). Examination of land use/land cover changes, urban growth dynamics, and environmental sustainability in Chittagong city, Bangladesh. *Environment, Development and Sustainability*, *18*(3), 697–716. https://doi.org/10.1007/s10668-015-9672-8

Islam, M. S., & Ahmed, R. (2011). Land Use Change Prediction In Dhaka City Using Gis Aided Markov Chain Modeling. *Journal of Life and Earth Science*, *6*, 81–89. https://doi.org/10.3329/jles.v6i0.9726

Kafy, A.-A., Faisal, A.-A.-, Shuvo, R. M., Naim, Md. N. H., Sikdar, Md. S., Chowdhury, R. R., Islam, Md. A., Sarker, Md. H. S., Khan, Md. H. H., & Kona, M. A. (2021). Remote sensing approach to simulate the land use/land cover and seasonal land surface temperature change using machine learning algorithms in a fastest-growing megacity of Bangladesh. *Remote Sensing Applications: Society and Environment*, *21*, 100463. https://doi.org/10.1016/j.rsase.2020.100463

Liu, H., Homma, R., Liu, Q., & Fang, C. (2021). Multi-Scenario Prediction of Intra-Urban Land Use Change Using a Cellular Automata-Random Forest Model. *ISPRS International Journal of Geo-Information*, *10*(8), Article 8. https://doi.org/10.3390/ijgi10080503

Liu, M., Wei, H., Dong, X., Wang, X.-C., Zhao, B., & Zhang, Y. (2022). Integrating Land Use, Ecosystem Service, and Human Well-Being: A Systematic Review. *Sustainability*, *14*(11), Article 11. https://doi.org/10.3390/su14116926

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *Land Use Policy*, *91*, 104414. https://doi.org/10.1016/j.landusepol.2019.104414

McDermott, C. L., Montana, J., Bennett, A., Gueiros, C., Hamilton, R., Hirons, M., Maguire-Rajpaul, V. A., Parry, E., & Picot, L. (2023). Transforming land use governance: Global targets without equity miss the mark. *Environmental Policy and Governance*, *33*(3), 245–257. https://doi.org/10.1002/eet.2027

Mendoza-Ponce, A., Corona-Núñez, R. O., Nava, L. F., Estrada, F., Calderón-Bustamante, O., Martínez-Meyer, E., Carabias, J., Larralde-Corona, A. H., Barrios, M., & Pardo-Villegas, P. D. (2021). Impacts of land management and climate change in a developing and socioenvironmental challenging transboundary region. *Journal of Environmental Management*, *300*, 113748. https://doi.org/10.1016/j.jenvman.2021.113748

Papaioannou, G., Alamanos, A., & Maris, F. (2023). Evaluating Post-Fire Erosion and Flood Protection Techniques: A Narrative Review of Applications. *GeoHazards*, *4*(4), Article 4. https://doi.org/10.3390/geohazards4040022

Pignotti, G., Rathjens, H., Cibin, R., Chaubey, I., & Crawford, M. (2017). Comparative Analysis of HRU and Grid-Based SWAT Models. *Water*, *9*(4), Article 4. https://doi.org/10.3390/w9040272

Qin, X., & Fu, B. (2020). Assessing and Predicting Changes of the Ecosystem Service Values Based on Land Use/Land Cover Changes With a Random Forest-Cellular Automata Model in Qingdao Metropolitan Region, China. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 6484–6494. https://doi.org/10.1109/JSTARS.2020.3029712

Roy, P., Chandra Pal, S., Chakrabortty, R., Chowdhuri, I., Malik, S., & Das, B. (2020). Threats of climate and land use change on future flood susceptibility. *Journal of Cleaner Production*, *272*, 122757. https://doi.org/10.1016/j.jclepro.2020.122757

Saputra, M. H., & Lee, H. S. (2019). Prediction of Land Use and Land Cover Changes for North Sumatra, Indonesia, Using an Artificial-Neural-Network-Based Cellular Automaton. *Sustainability*, *11*(11), Article 11. https://doi.org/10.3390/su11113024

St. Joseph River Watershed Initiative (2005). Cedar Creek Watershed Management Plan. Indiana Department of Environmental Management, 2005.

Tariq, A., & Shu, H. (2020). CA-Markov Chain Analysis of Seasonal Land Surface Temperature and Land Use Land Cover Change Using Optical Multi-Temporal Satellite Data of Faisalabad, Pakistan. *Remote Sensing*, *12*(20), Article 20. https://doi.org/10.3390/rs12203402

Ulloa-Espíndola, R., & Martín-Fernández, S. (2021). Simulation and Analysis of Land Use Changes Applying Cellular Automata in the South of Quito and the Machachi Valley, Province of Pichincha, Ecuador. *Sustainability*, *13*(17), Article 17. https://doi.org/10.3390/su13179525

USGS. (2021). *National Land Cover Database | U.S. Geological Survey*. National Land Cover Database. Retrieved October 20, 2023, from https://www.usgs.gov/centers/eros/science/national-land-cover-database

Wallace, C. W., Flanagan, D. C., & Engel, B. A. (2018). Evaluating the Effects of Watershed Size on SWAT Calibration. *Water*, *10*(7), Article 7. https://doi.org/10.3390/w10070898

Xing, W., Qian, Y., Guan, X., Yang, T., & Wu, H. (2020). A novel cellular automata model integrated with deep learning for dynamic spatio-temporal land use change simulation. *Computers & Geosciences*, *137*, 104430. https://doi.org/10.1016/j.cageo.2020.104430

Zambrano-Asanza, S., Morales, R. E., Montalvan, J. A., & Franco, J. F. (2023). Integrating artificial neural networks and cellular automata model for spatial-temporal load forecasting. *International Journal of Electrical Power & Energy Systems*, *148*, 108906. https://doi.org/10.1016/j.ijepes.2022.108906